Utrecht University

B3CC: Concurrency

11: Accelerate

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Announcement

- Welcome back!
- The third practical is now available
  - Due Friday 26 January @ 23:59
  - You may work in pairs

Scaling and Speedup

Leftovers from 09: Parallelism

Speedup

- The performance improvement, or *speedup* of a parallel application, is:
  - Where T_P is the time to execute using *P* threads/processors

$$\text{speedup} = S_P = \frac{T_1}{T_P}$$

- The *efficiency* of the program is:

$$\text{efficiency} = \frac{S_P}{P} = \frac{T_1}{P\,T_P}$$

- Here, T_1 can be:
  - The parallel algorithm executed on one thread: *relative speedup*
  - An equivalent serial algorithm: *absolute speedup*

Maximum speedup

- Several factors appear as overhead in parallel computations and limit the speedup of the program
  - Periods when not all processors are performing useful work
  - Extra computations in the parallel version not appearing in the sequential version (example: recompute constants locally)
  - Communication time between processes

Amdahl

- The execution time (T_1) of a program splits into:
  - W_{ser}: time spent doing (non-parallelisable) serial work
  - W_{par}: time spent doing parallel work

$$T_P \geq W_{\text{ser}} + \frac{W_{\text{par}}}{P}$$

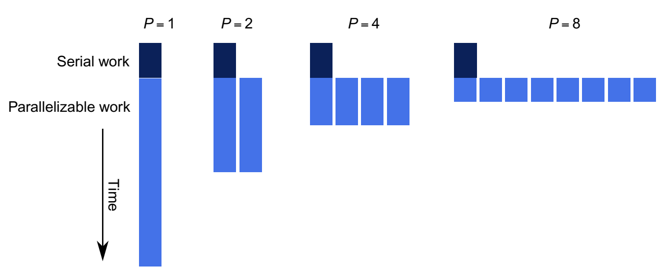
- If $f = \frac{W_{\text{ser}}}{W_{\text{ser}} + W_{\text{par}}}$ is the fraction of serial work to be performed, we get the parallel speedup:

$$S_P \leq \frac{1}{f + (1-f)/P}$$

- This is called *Amdahl's Law*

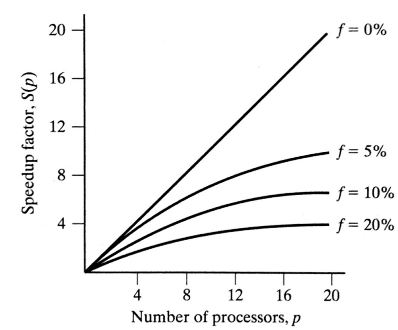
Amdahl

- The speedup bound is determined by the degree of sequential execution in the program, not the number of processors
  - *Strong scaling* (fixed-sized speedup): $\lim_{P\to\infty} S_P \leq 1/f$



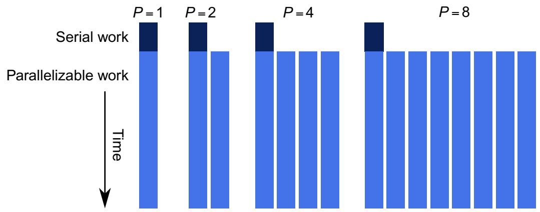
Amdahl

- The serial fraction of the program limits the achievable speedup



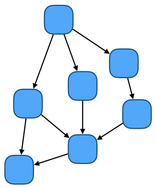
Gustafson-Barsis

- Often the problem size can increase as the number of processes increases
  - The proportion of the serial part decreases
  - *Weak scaling* (scaled speedup): $S'_P = f + (1 - f)P$



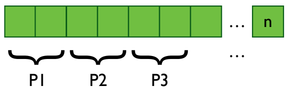
Data parallelism, GPU programming

Recap



Task parallelism

- Explicit threads
- Synchronise via locks, messages, or STM
- Modest parallelism
- Hard to program



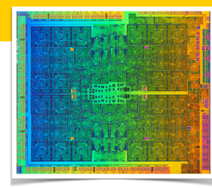
Data parallelism

- Operate simultaneously on bulk data
- Implicit synchronisation
- Massive parallelism
- Easy to program

Recap

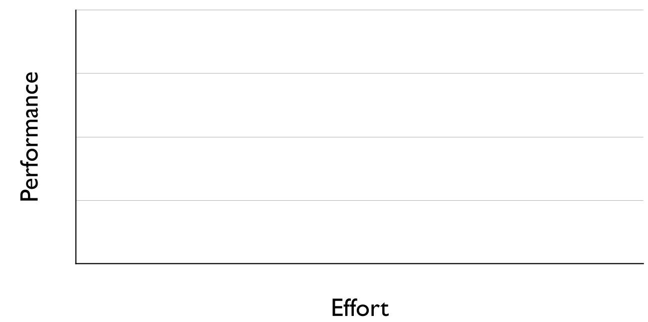
- Despite the name, data parallelism is only a programming model
  - The key is a *single logical thread of control*
  - It does not actually require the operations to be executed in parallel!
  - Today we'll look at a language for data-parallel programming on the GPU

GPU (graphics processing unit)

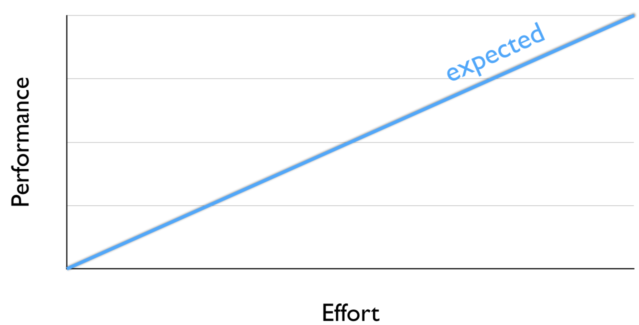


- Lots of interest to use them for non-graphics tasks
  - Machine learning, bioinformatics, data science, weather & climate, medical imaging, computational chemistry, …
  - Can have much higher performance than a traditional CPU
- Specialised hardware with a specialised programming model
  - Caches are software programmable; must be wary of associativity
  - Memory management is explicit, with distinct memory spaces
  - Thousands of threads running simultaneously, each of which can modify any piece of memory at any time

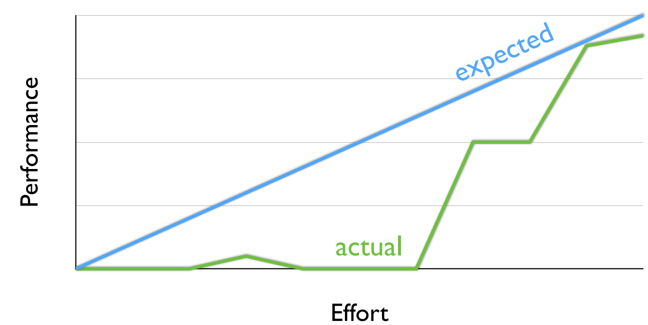
GPU programming



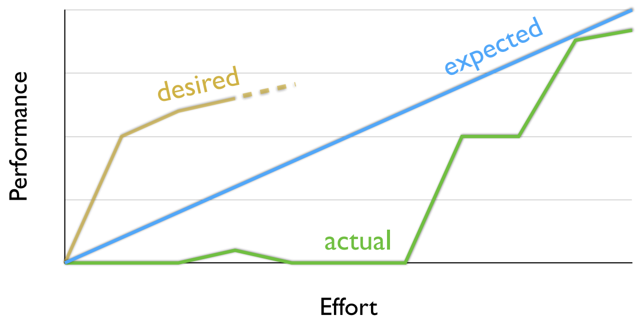
GPU programming



GPU programming

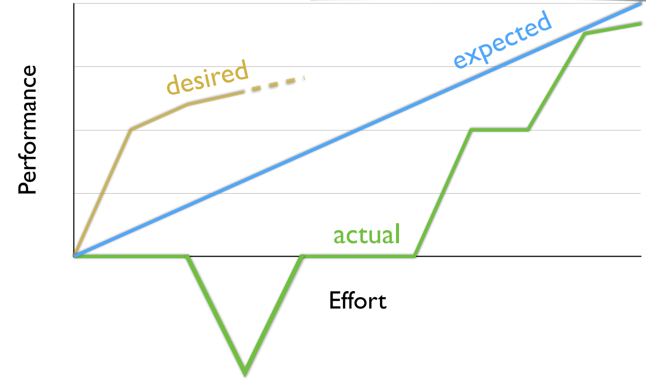


GPU programming



GPU programming

After expressing available parallelism, I often find that the code has slowed down.
— Jeff Larkin, NVIDIA Developer Technology



https://devblogs.nvidia.com/getting-started-openacc/

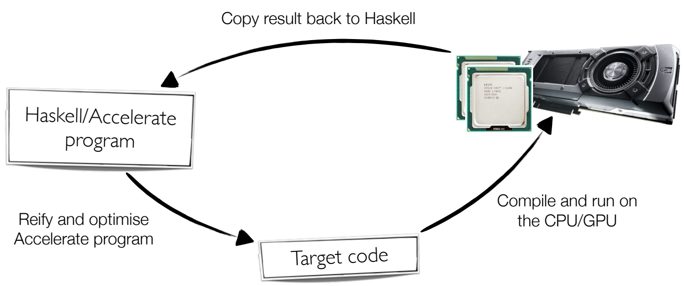
GPU programming

- Two main difficulties:
  1. Structuring the program in a way suitable for GPU parallelisation ⟵
  2. Writing (performant) GPU code

Accelerate

Accelerate

- An embedded language for *data-parallel arrays* in Haskell
  - Takes care of generating the high-performance CPU/GPU code for us
  - Computations take place on dense multi-dimensional arrays
  - Parallelism is introduced in the form of collective operations on arrays



Accelerate

- Computations take place on arrays
  - Parallelism is introduced in the form of collective operations over arrays
  - map, zipWith, fold, scan (various kinds); permutations (data movement); etc.
  - It is a *restricted* language: consists only of operations which can be executed efficiently in parallel
  - Different types to distinguish parallel computations from scalar expressions

Example: dot product

- In Haskell (lists):

```
import Prelude

dotp :: Num a
     => [a]
     -> [a]
     -> a
dotp xs ys = foldl’ (+) 0 (zipWith (*) xs ys)
```


Example: dot product

- In Accelerate:

```
import Data.Array.Accelerate

dotp :: Num a
     => Acc (Vector a)
     -> Acc (Vector a)
     -> Acc (Scalar a)
dotp xs ys = fold (+) 0 (zipWith (*) xs ys)
```

Example: dot product

- In Accelerate:

Dimensionality

Element type

`Int`, `Float`, `(a,b)`, `Maybe a`, etc.

```
import Data.Array.Accelerate

dotp :: Num a
     => Acc (Array DIM1 a)
     -> Acc (Array DIM1 a)
     -> Acc (Array DIM0 a)
dotp xs ys = fold (+) 0 (zipWith (*) xs ys)
```

```
Scalar a = Array DIM0 a = Array Z a
Vector a = Array DIM1 a = Array (Z :. Int) a
Matrix a = Array DIM2 a = Array (Z :. Int :. Int) a
           Array DIM3 a = Array (Z :. Int :. Int :. Int) a
             ...
```


Accelerate

- Compile and execute an Accelerate program
  - The same program can be run on different targets

```
import Data.Array.Accelerate.Interpreter
-- import Data.Array.Accelerate.LLVM.Native
-- import Data.Array.Accelerate.LLVM.PTX

run  :: Arrays a => Acc a -> a
runN :: Afunction f => f -> AfunctionR f

runN :: (…) => Acc a -> a
runN :: (…) => (Acc a -> Acc b) -> a -> b
runN :: (…) => (Acc a -> Acc b -> Acc c) -> a -> b -> c
-- ...
```

There's also `runQ`, but don't worry about that

Accelerate

- Parallel computations take place on arrays
  - A *stratified* language of parallel (`Acc`) and scalar (`Exp`) computations
  - Parallel operations consist of many scalar expressions executed in parallel

Accelerate

- The `map` operation:
  - A collective operation (`Acc`) which applies the given scalar function (`Exp`) to each element of the array *in parallel*
  - `map (\x -> x+1) xs` on a one-dimensional array of floats:

Acc

```
__global__ void map( float* d_xs, float* d_ys, int len )
{
   int i = blockDim.x * blockIdx.x + threadIdx.x;
   if ( i < len ) {
      float x = d_xs[i];
      d_ys[i] = x + 1;
   }
}
```

Exp

Accelerate

- The `map` operation:
  - A collective operation (`Acc`) which applies the given scalar function (`Exp`) to each element of the array *in parallel*

"an array index type" *"an array element type"*

```
map :: (Shape sh, Elt a, Elt b)
    => (Exp a -> Exp b)
    -> Acc (Array sh a)
    -> Acc (Array sh b)
```


Oddities

- Accelerate is a language *embedded* in Haskell
  - We reuse much of the syntax, but the semantics are different
    - Strict evaluation, unboxed data, no general recursion…
  - Actually, `Acc` and `Exp` are just data structures!
    - Have a `Show` instance
    - The Haskell program *generates* the Accelerate program
    - The `run` operation performs runtime (cross) compilation
  - But the integration has some oddities as well…

Lifting & Unlifting

- Consider the following two types:

```
x :: (Exp Int, Exp Int)
y :: Exp (Int, Int)
```

  - The first is a Haskell pair of embedded expressions on `Int`
  - The second is an embedded expression returning a pair of `Int`s
- How to convert between the two?
  - The pattern synonym `T2`
  - (legacy: the functions `lift` and `unlift` (not recommended))

Pattern synonyms

- We use pattern synonyms for constructing & destructing embedded tuples
  - Can't overload built-in syntax (,), (, ,), etc.
  - Instead we use `T2`, `T3`, etc. at both the `Acc` and `Exp` level

```
result :: Acc (Vector Int, Scalar Int)
result = …

T2 idx tot = result
  -- idx :: Acc (Vector Int)
  -- tot :: Acc (Scalar Int)

res = T2 tot idx
  -- res :: Acc (Scalar Int, Vector Int)
```

Shapes

- Array shapes (& indices) are snoc-lists formed from `Z` and `(:.)`
  - `Z` is a zero-dimensional (scalar)
  - `(:.)` adds one inner-most dimension on the right

```
type DIM1     = Z :. Int
type Vector a = Array DIM1 a
```

- More pattern synonyms for constructing & destructing indices

```
x    :: Exp Int
I1 x :: Exp DIM1   -- you’ll need this one
```


Pattern matching

- Use the `match` operator to perform pattern matching in embedded code
  - Also note the pattern synonyms for constructing/deconstructing cases

```
foo :: Exp (Maybe Int) -> Exp Int
foo x = x & match \case
  Nothing_ -> 0
  Just_ y  -> y + 1
```


Guards

- Unfortunately guard syntax doesn’t work
  - Use a regular if-then-else (chain) instead

```
nope :: Exp Int -> Exp Int
nope x
  | x < 0     = ...
  | otherwise = ...
```


Looping

- Can’t write recursive embedded functions directly
  - Need to use an explicit (tail-recursive) looping combinator instead
  - Continue applying the body function (second argument) as long as the predicate function (first argument) returns true

```
awhile
  :: Arrays a
  => (Acc a -> Acc (Scalar Bool))
  -> (Acc a -> Acc a)
  -> Acc a
  -> Acc a
```

Debugging

- Some trace functions for printf-style debugging
  - Output a trace message as well as some arrays to the console before proceeding with the computation
  - Useful for inspecting intermediate values

```
atraceArray
  :: (Arrays a, Arrays b)
  => Text      ← use "quotes"
  -> Acc a
  -> Acc b
  -> Acc b
```


Documentation

- More information in the documentation
  - https://ics.uu.nl/docs/vakken/b3cc/resources/acc-head-docs (latest version, used in the Quickhull template)
  - https://hackage.haskell.org/package/accelerate (released version (older))

Accelerate

- Implementing a data-parallel program consists of two parts:
  - What are the collective (parallel) operations that need to be done?
  - What does each individual (sequential) thread need to do?

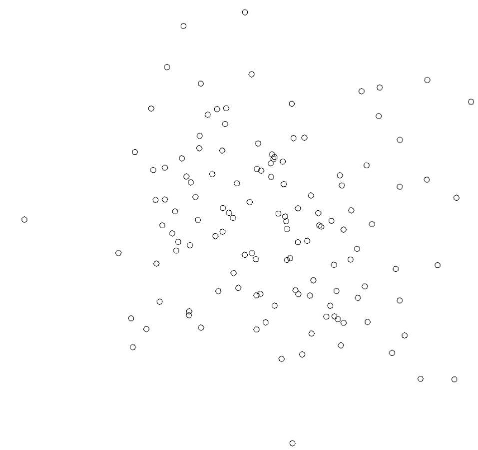
Quickhull

Quickhull

- An algorithm to determine the small polygon containing a set of points
  - You will implement a data-parallel version of the algorithm in Accelerate
  - See the specification for details

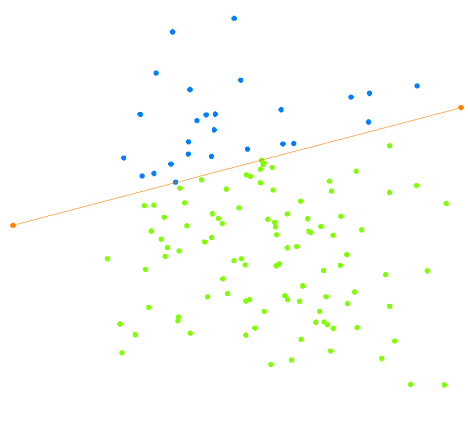
Example

- Initial points
  - The goal is to find the smallest polygon containing all these points
  - This is known as the *convex hull*



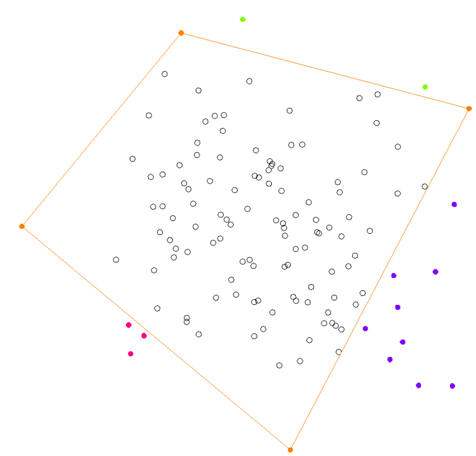
Example

- Create initial partition
  - Choose two points that are definitely on the convex hull
  - Partition others to either side of that line (above/left and below/right)
  - Points of the same colour are in the same segment



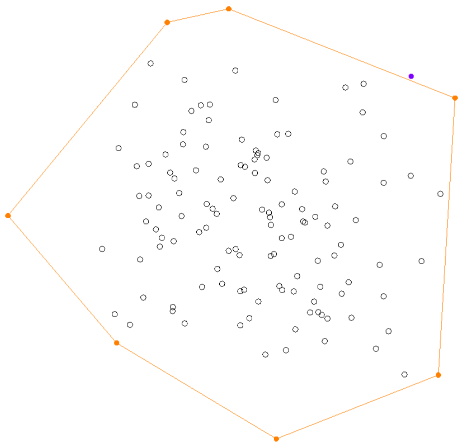
Example

- Recursively partition each segment
  - This is done for all points at once, in data-parallel
  - The hollow circles are points no longer under consideration
  - Orange circles are on the convex hull
  - Other colours are still undecided.
  - Same colours are in the same partition



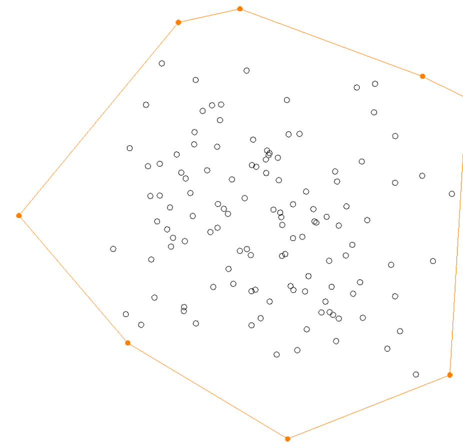
Example

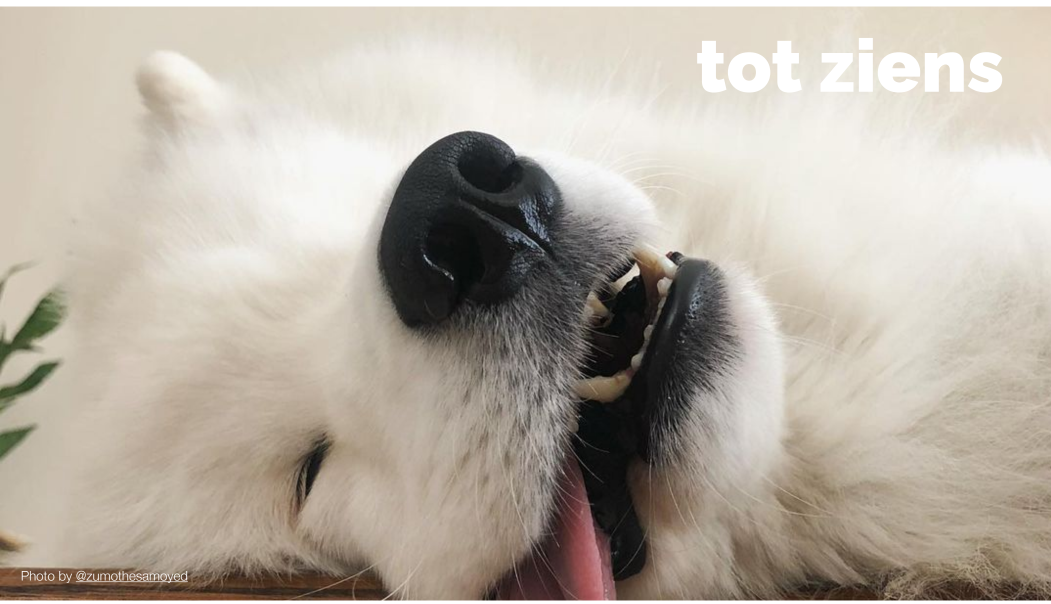
• Continue partitioning each segment…



Example

• … until no undecided points remain





Traditional compiler construction

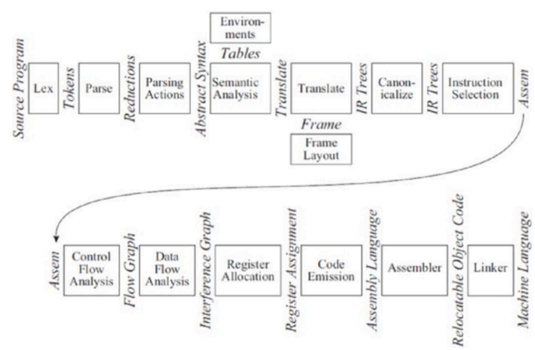


FIGURE 1.1. Phases of a compiler, and interfaces between them

Modern Compiler Implementation in Java, A. Appel and J. Palsberg

Modern compiler construction

FIGURE 1.1. Phases of a compiler, and interfaces between them